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Evaluation of a Wildfire Smoke Forecasting System as a Tool for Public Health Protection

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Abstract

Background: Exposure to wildfire smoke has been associated with cardiopulmonary health impacts. Climate change will increase the severity and frequency of smoke events, suggesting a need for enhanced public health protection. Forecasts of smoke exposure can facilitate public health responses.

Objectives: To evaluate the utility of a wildfire smoke forecasting system (BlueSky) for public health protection by comparing its forecasts with observations and assessing their associations with population-level indicators of respiratory health in British Columbia, Canada.

Methods: We compared BlueSky $PM_{2.5}$ forecasts with $PM_{2.5}$ measurements from air quality monitors, and BlueSky smoke plume forecasts with plume tracings from remote sensing data (HMS). Daily counts of salbutamol dispensations and asthma-related physician visits were aggregated for each geographic local health area (LHA). Daily continuous measures of $PM_{2.5}$ and binary measures of smoke plume presence, either forecasted or observed, were assigned to each LHA. Poisson regression was used to estimate the association between exposure measures and health indicators.

Results: We found modest agreement between forecasts and observations, which was improved during intense fire periods. A 30μg/m^3 increase in BlueSky $PM_{2.5}$ was associated with 8% increase in salbutamol dispensations and 5% increase in asthma-related physician visits. BlueSky plume coverage was associated with 5% and 6% increases in the two health indicators, respectively. The effects were similar for observed smoke, and generally higher in very smoky areas.

Conclusions: BlueSky forecasts showed modest agreement with retrospective measures of smoke, and were predictive of respiratory health indicators, suggesting they can provide useful information for public health protection.

INTRODUCTION

As the global climate continues to change, more frequent and intense wildfire events and longer wildfire seasons are expected (Flannigan and Wagner 1991; Wotton et al. 2010; Wotton and Flannigan 1993).Wildfire smoke can degrade local, regional and global air quality (Dirksen et al. 2009; Dutkiewicz et al. 2011; Viswanathan et al. 2006). Exposure to wildfire smoke has been associated with cardiopulmonary health effects, with the most consistent associations found for respiratory outcomes (Dennekamp and Abramson 2011), including dispensations of reliever medications (Caamono-Isora 2011; Elliott et al. 2013), physician and emergency room visits (Henderson et al. 2011; Rappold et al. 2011; Lee et al. 2009), and hospital admissions (Delfino et al. 2009; Henderson et al. 2011; Morgan et al. 2010; Tham et al. 2009; Johnston et al. 2007).

Among the different constituents of the complex smoke mixture, $PM_{2.5}$ (particulate matter < 2.5 μm in aerodynamic diameter) has been the most consistently elevated and widely measured exposure metric (Naeher et al. 2007; Sapkota et al. 2005). Tools conventionally used for estimating wildfire smoke exposures include surface $PM_{2.5}$ monitoring and remote sensing products such as the Hazard Mapping System (HMS), which produces hand-drawn smoke plumes by integrating images from multiple satellites (US Department of Commerce 2013). These tools, however, have important limitations. For example, while monitoring networks may accurately reflect ground-level $PM_{2.5}$ concentrations with adequate temporal resolution, they typically do not cover all populated areas affected by fire smoke, and monitors can fail when affected by heavy smoke or actual fire. On the other hand, data from remote sensing products may cover vast geographic areas, but they cannot measure ground-level concentrations, they have different sampling frequencies, and observations can be obscured by clouds. Furthermore, both of these tools only provide retrospective or near-real-time observations. From the perspective of supporting public health response during wildfire smoke episodes, prospective information is more desirable.

Forecasts have been implemented for many health hazards, such as extreme heat (Hajat et al. 2010), pollen (Pasken and Pietrowicz 2005), and UV radiation (Burrows et al. 1994). An important motivation for forecasting tools is to provide prospective information for public health actions to mitigate the adverse impacts before the hazards actually occur. To support the utility of forecasts for health protection, it is important to know (1) whether forecasts are accurate and precise compared with reference measurements, and (2) whether forecasts are associated with population health responses. Most evaluations of forecasting models address only the first question, but for an exposure without a "gold-standard" reference measurement, like wildfire smoke, answering the second question is also important. Here we address both questions in an integrated evaluation of the operational BlueSky Western Canada Wildfire Smoke Forecasting Framework (BlueSky).

BlueSky (http://www.bcairquality.ca/bluesky/) has produced publicly available forecasts of $PM_{2.5}$ concentrations from wildfires up to 60 hours in advance since 2010. Detailed information about the system is described elsewhere (Sakiyama 2013). Briefly, meteorological forecasts, fire locations, fuel consumption estimates, and smoke emissions estimates are combined in a dispersion model to estimate resulting ground-level $PM_{2.5}$ concentrations in the modeling domain (Figure 1). To date there has been no systematic, quantitative evaluation of general BlueSky performance or of the associations between BlueSky output and population health indicators.

Here we compare the $PM_{2.5}$ concentrations forecasted by BlueSky with those measured by the ambient air quality monitoring network, and we compare the plume shapes forecast by BlueSky with those observed by HMS. We then assess whether respiratory reliever dispensations and asthma-related physician visits show the expected associations with BlueSky forecasts, based on known associations with observed data.

METHODS

Study area and period

This study covers the province of British Columbia (BC) in Canada, which is divided into 89 local health areas (LHAs) for administrative purposes (Figure 1). The study period was 35 days between 24 July and 29 August 2010, which captured the entire active fire season. Based on area burned, the 2010 fire season was the worst on record in BC. More than 330,000 hectares of forest were burned (Wildfire management branch 2013), with the central interior region most severely impacted (Figure 1).

Data description

BlueSky $PM_{2.5}$: The daily average of $PM_{2.5}$ concentrations forecast by BlueSky 48-hours in advance. Although BlueSky produces $PM_{2.5}$ forecasts up to 60-hours in advance, we present results for the 48-hour forecasts because this is a relevant averaging period from the public health perspective.

Monitor $PM_{2.5}$: Hourly $PM_{2.5}$ measurements from 36 monitoring stations (32 Tapered Element Oscillating Microbalances, 4 beta attenuation monitors) in BC (Figure 1) were retrieved from the BC Ministry of Environment (BC Ministry of Environment 2012). Midnight-to-midnight 24-hour average concentrations were calculated at each location. The average for any date with 6 hourly measurements missing in total or 3 missing consecutively was set to missing. When the filter pressure (a measure of the load on the sampler) was larger than 60%, the sampler was overloaded and the measurement of PM was not reliable, so these data were also set to missing.

BlueSky Plumes: Daily smoke plume shapes were derived from the outline of all BlueSky $PM_{2.5}$ forecasting grid cells (0.1 degree resolution, about 10 x 10 km) with daily mean $PM_{2.5}$ values larger than zero.

HMS Plumes: Daily images of smoke plumes from HMS were retrieved from the National Oceanic and Atmospheric Administration (NOAA) (http://www.firedetect.noaa.gov/viewer.html). These plumes were hand-drawn by trained NOAA analysts based on imagery from seven satellites

(Ruminski et al. 2006), and each plume was assigned to one of the three semi-quantitative smoke density categories. For this study we combined all plumes, regardless of their density categories, observed at different times within a single day to represent areas that had been covered by any HMS plume during any time in that day.

Population health indicators: Previous studies have reported significant increases in salbutamol dispensations (Elliott et al. 2013) and asthma-related physician visits (Henderson et al. 2011) during forest fire smoke episodes in BC. We used similar data to evaluate whether BlueSky output was associated with the same population health indicators. Salbutamol sulfate is commonly used for relief of acute bronchospasm in conditions such as asthma and chronic obstructive pulmonary disease. Daily counts of the dispensations were extracted from the BC PharmaNet database (BC Ministry of Health 2013a) for 85 of the 89 LHAs. Data were not available for four LHAs with populations less than 1,000 persons (Figure 1). Outpatient physician visits for asthma are coded as 493 in the International Classifications of Diseases, 9th revision (World Health Organization 1975). Daily counts were extracted from the BC Medical Services Plan billings database (BC Ministry of Health 2013b) for 73 of the 89 LHAs. Data were not available for 16 LHAs located in the Vancouver Island Health Authority (Figure 1). These two health indicators were divided by the estimated total population of the corresponding LHA in 2010 (BC Stats 2011), resulting in daily rates for each of the LHAs. The overall asthma reliever dispensation and physician visit rates across the province during the study period were 34 and 9.3 per 100,000 person-days, respectively. Both rates decreased during weekends/holidays (18 for salbutamol dispensations and 3.9 for asthma-related physician visits per 100,000 person-days) compared with weekdays (42.7 and 12.3 per 100,000 person-days). A large range of outcomes rates was observed across different LHAs, from 17.7 to 72.2 for salbutamol dispensations, and from 2.7 to 21.1 for asthma-related physician visits.

Exposure assignment

The health indicator data were aggregated to the LHA level, and we assigned four exposure variables to each LHA for each day of the study period: BlueSky $PM_{2.5}$; Monitor $PM_{2.5}$; BlueSky Plume; and HMS Plume. Because some LHAs cover large geographic areas, we used census dissemination areas (DAs) to estimate population-weighted exposures. One DA typically includes 400 to 700 people (Statistics Canada 2012), and each LHA contained the geographic centers of multiple DAs, ranging from 3 to 474. We calculated the population-weighted average BlueSky $PM_{2.5}$ and Monitor $PM_{2.5}$ for each LHA using the values at (BlueSky) or nearest to (monitoring stations) the DA centroids. We also overlaid BlueSky Plumes and HMS Plumes with the DA centroids, and LHAs with more than 50% of the total population covered by the smoke plumes were assigned a value of 1, otherwise a 0. As a result, two continuous variables (BlueSky $PM_{2.5}$ and Monitor $PM_{2.5}$) and two binary variables (BlueSky Plumes and HMS Plumes) were created.

Statistical analyses

Four model evaluation statistics were calculated for the relationship between BlueSky $PM_{2.5}$ and Monitor $PM_{2.5}$: the Pearson's correlation coefficient (r), normalized root mean squared error (NRMSE), index of agreement (IOA, varying from 0 to 1 where a value of 1 indicates a perfect match), and fractional bias (FB, difference between observation and forecast divided by the average of the two). These statistics were calculated in three different analyses: a global analysis, in which all forecasted and measured values at any time and location were included; a spatial-only analysis, in which forecasted and measured values were compared at fixed times for all locations; and a temporal-only analysis, in which whole time series of forecasted and measured values were compared for fixed locations. To quantitatively assess the extent of agreement between BlueSky and HMS plumes, the figure of merit in space (FMS) (Mosca et al. 1998) was calculated. FMS is calculated as the areas of intersection ($A_{BlueSky} \cap A_{HMS}$, area covered by both BlueSky and HMS plumes) and union ($A_{BlueSky} \cup A_{HMS}$, area covered by BlueSky and/or HMS plumes) of the two plumes for each day (Equation 1).

$$FMS = A_{BlueSky} \cap A_{HMS} / A_{BlueSky} \cup A_{HMS} \times 100\% \qquad [1]$$

We used Poisson regression to estimate the effects of smoke exposure on rates of salbutamol dispensations and asthma-related physician visits. For the continuous variables the effect was estimated for a 30 $\mu g/m^3$ increase in $PM_{2.5}$, which was equivalent to two standard deviations in the daily $PM_{2.5}$ concentrations measured across all monitoring stations. For the binary variables, the effect of being covered by the smoke plume was compared with not being covered. To account for potential autocorrelation within the time-series data from any individual LHA, parameters in the regression models were calculated with generalized estimation equations (GEE) in R (R Core Team, Vienna, Austria), assuming an exchangeable correlation structure (where the correlation between all pairs of daily measures within-LHA was uniform and non-zero). Model estimates were adjusted for daily maximum temperature from the closest monitor to each LHA, day of week, holidays, and the week of the study period. A lag of 0-1 days was used for all analyses, based on the best fitted lag time for the acute effects from forest fire smoke in previous BC fire smoke studies (Elliott et al. 2013). The average of the same day and previous day concentrations was used for PM2.5, and for the plumes a 1 was assigned if either the same day and/or the previous day had 50% of the population covered.

We also conducted sensitivity analyses to compare areas based on degree of smokiness. Very smoky areas were defined as LHAs covered by HMS smoke plumes for ≥ 12 days (the mean number of days with HMS smoke plumes covering 50% of the population in an LHA), and less smoky areas were defined as other LHAs.

RESULTS

BlueSky $PM_{2.5}$ vs. Monitor $PM_{2.5}$

Model evaluation statistics for BlueSky $PM_{2.5}$ forecasts compared with monitored $PM_{2.5}$ observations showed modest agreement (Table 1). Bland-Altman plots (excluding pairs with zero BlueSky forecasts) indicated that the disagreement between BlueSky $PM_{2.5}$ and Monitor $PM_{2.5}$ was largely attributable to BlueSky over-predictions (Figure 2), also indicated by the negative fractional bias (Table 1). The spatial analyses (Table 1) showed wide ranges in the comparison statistics, suggesting high temporal variability in the spatial agreement, although the time series plots suggested better agreement during major fire periods (see example of IOA in Figure 3). There was similar variation in comparison statistics for the temporal analyses (Table 1), indicating differing degrees of agreement at different locations. A larger range of NRMSE in the spatial analyses indicated more inconsistent day-to-day spatial agreement than the temporal agreement over all locations.

The mean Monitor $PM_{2.5}$ ranged from 0.02 to 176.4 $\mu g/m^3$ across the LHAs. The arithmetic mean (standard deviation) concentration was 10.0 (14.5) $\mu g/m^3$, with an interquartile range between 3.0 and 10.1 $\mu g/m^3$. The mean BlueSky $PM_{2.5}$ forecast ranged from 0 to 988 $\mu g/m^3$ across the LHAs. The arithmetic mean was 4.0 (27.3) $\mu g/m^3$ with an interquartile range between 0 and 0.1 $\mu g/m^3$. The distribution of BlueSky $PM_{2.5}$ was highly skewed due to the large number of zero values in the output. This distribution is typical for air quality model outputs (Mosca et al. 1998), and emphasized for models that only account for one emissions source.

The rate ratios (RRs) for salbutamol dispensations were 1.08 (95% CI: 1.06, 1.10) for a 30 μg/m^3 increase in BlueSky $PM_{2.5}$ and 1.12 (95% CI: 1.07, 1.17) for a 30 μg/m^3 increase in Monitor $PM_{2.5}$ (Table 2). The RRs for asthma-related physician visits were 1.05 (95% CI: 1.01, 1.09) for BlueSky $PM_{2.5}$ and 1.10 (95% CI: 1.00, 1.21) for Monitor $PM_{2.5}$. Larger point estimates and wider confidence intervals were observed for the Monitor $PM_{2.5}$ compared with the BlueSky $PM_{2.5}$, partially due to some very high concentrations (up to 988 μg/m^3) forecast by BlueSky. The difference between the two was attenuated when BlueSky $PM_{2.5}$ estimates over 300 μg/m^3 were truncated to 300 μg/m^3 (Table 2). In the sensitivity analysis, we found significant associations in very smoky areas, and no associations in less smoky areas for both health outcome indicators (Figure 4).

BlueSky Plumes vs. HMS Plumes

The mean areas of BlueSky Plumes and HMS Plumes during the study period were 153,200 and 334,500 square kilometer (km^2), respectively. BlueSky generally forecasted smaller smoke plumes than those observed by HMS during major fire events. The mean FMS score was 0.21, with a range of 0 to 0.52. Higher FMS scores were observed during the major fire event periods (Figure 3).

The number of days with 50% or more of the population covered by HMS Plumes ranged from 4 to 21 (out of 35) across the LHAs, with a mean of 12 days. The mean number of days with 50% or more of the population covered by BlueSky Plumes was 9 (out of 33), with a range of 2 to 21 days. Although the study period was 35 days, two days of BlueSky forecasts were missing

The RRs for salbutamol dispensations associated with BlueSky and HMS Plumes were very similar, both with a point estimate of 1.05 (Table 2). The RR for physician visits was 1.06 (95% CI: 0.99, 1.15) for BlueSky Plume coverage and 1.09 (95% CI: 1.02, 1.18) for HMS Plume coverage. In the sensitivity analysis for salbutamol dispensations, we also found significant associations in very smoky areas, and no associations in less smoky areas. The same was not observed for the physician visits (Figure 4).

DISCUSSION

This is the first study to assess a smoke forecasting system for public health protection by (1) comparing its output with observations from other air quality assessment tools, and (2) evaluating associations between its output and health indicators known to be associated with those other air quality assessment tools. During short-term air pollution episodes, such as wildfire smoke events, different strategies (ranging from public education to community evacuation) may be implemented based on assessment of exposure levels and their corresponding health risks. BlueSky is one of the many tools available for smoke exposure assessment, but it is different from the other tools because it provides a forecast rather than an observation in near-real-time or a retrospective measure. This study helps to highlight the potential role of smoke forecasting systems in the public health response process.

We found modest agreement between BlueSky $PM_{2.5}$ and Monitor $PM_{2.5}$, with a global correlation of 0.4. The results compared well with correlations of 0.3 and 0.5 between forecasts from the two branches of the European Fire Assimilation System and the MODIS $PM_{2.5}$ observations (Sofiev et al. 2009). In the comparison of BlueSky Plumes and HMS Plumes, the daily FMS scores ranged from 0 to 0.60 with a mean of 0.18. These scores were slightly higher than the results reported in Stein et al. (2009) for three fire events, where the FMS scores between the US NOAA smoke forecasts and HMS observations ranged from 0.02 to 0.40, with a mean of 0.14. In our study, generally better agreement was observed during intense fire periods, indicated by all evaluation statistics we used.

Disagreement between BlueSky forecasts and observed data could come from the limitations of the BlueSky system, including its inability to predict smoke from fires outside of the modeling domain, and uncertainty in the input meteorology and/or fire information. However, limitations of the HMS plumes and measured $PM_{2.5}$ concentrations are also important, as these tools are not "gold standards" for wildfire smoke exposure assessment, or for evaluating BlueSky forecasts. For example, we delineated the shape of BlueSky plume forecasts using all areas where surface concentration estimates were greater than zero, but the HMS plumes are observed by satellites and therefore reflect smoke in the total column of the atmosphere. On the other hand, air quality monitoring stations capture $PM_{2.5}$ from all sources while BlueSky forecasts only the fraction of $PM_{2.5}$ attributable to smoke from wildfires within the modeling domain (Figure 1). Thus, monitor observations might reflect a large fraction of PM from other sources in areas with limited smoke, affecting the agreement with BlueSky.

We found 8% and 12% increases in salbutamol dispensations associated with 30 $\mu g/m^3$ increases in BlueSky and Monitor $PM_{2.5}$, respectively. The same increases in BlueSky and Monitor $PM_{2.5}$ were also associated with 5% and 10% increases in asthma-related physician visits. The RRs for BlueSky were smaller than but comparable with monitor observations in this study and other similar studies. Elliott et al. (2013) found a 30 $\mu g/m^3$ increase in monitor $PM_{2.5}$ was associated with 19% (95% CI: 12, 23%) increase in salbutamol dispensations in fire-affected populations of BC during the 2003 to 2010 fire seasons, using meta-regression from different LHAs. Henderson et al. (2011) reported that a 30 $\mu g/m^3$ increase in monitor-observed PM_{10} was associated with a 16% increase in the odds of an asthma-specific physician visit in a cohort of 280,000 people during the 2003 wildfire season in BC. Although Henderson et al. (2011) used PM_{10} instead of $PM_{2.5}$, the results are comparable because $PM_{2.5}$ is the major fraction of PM_{10} from wildfire smoke (Moore et al. 2006; Wu et al. 2006). In that same study, a 30-$\mu g/m^3$ increase in PM_{10} from wildfire smoke modeled by CALPUFF (in this case a retrospective model rather than an operational forecast) was associated with 2% increase of odds of asthma-specific physician visits. Delfino et al. (2009)

reported that a 30-µg/m^3 increase in $PM_{2.5}$ was associated with 16% increase in asthma hospital admissions in Los Angeles, California.

Although BlueSky $PM_{2.5}$ forecasts were consistently associated with health indicators and the effect estimates were comparable with Monitor $PM_{2.5}$ measurements, the estimated effects were generally smaller and the confidence intervals were narrower. An important contributor to this result was the large range of values in the BlueSky forecasts. When forecasts over 300 µg/m^3 were truncated to 300 µg/m^3 (approximately double the highest Monitor $PM_{2.5}$ concentration), the point estimates were larger and the confidence intervals were wider than those calculated with the original data (Table 2).

We also found a 5% increase in salbutamol dispensations associated with being covered by BlueSky or HMS Plumes. For asthma-related physician visits the increases were 6% and 9% for BlueSky and HMS Plumes, respectively. In the Henderson et al. (2011) cohort study, being covered by HMS plumes was associated with a 21% increase in the odds of an asthma-related physician visit. Rapplod et al. (2011) used aerosol optical depth measured by satellites to identify dense smoke plumes in North Carolina, US. A 65% increase in asthma-specific emergency department visits was observed for smoke-affected counties when exposed days were compared with non-exposed days.

Larger point estimates of association were found for salbutamol dispensations in more smoky areas compared with less smoky areas, but this was not observed for asthma-related physician visits. This may suggest the increase in dispensations was more relevant to wildfire smoke exposures. Although only a few wildfire smoke studies (Caamano-Isorna et al. 2011; Elliott et al. 2013) have reported using pharmaceutical dispensation as an indicator of population health, our results further support the use of this indicator for wildfire smoke research and surveillance. However, while dispensations appear to be sensitive to smoke exposure, it is unclear whether the observed associations were driven by actual health impacts or by people filling prescriptions to prepare for smoke events. This might also be true for the physician visits.

In conclusion, we found that agreement between BlueSky forecasts and observed data was reasonable compared with evaluations of other existing smoke forecasting systems. Better agreement was generally observed during intense fire periods. We also found significant associations between BlueSky forecasts and respiratory health outcomes, with risk estimates consistent with those calculated using the observed data, and with those reported by other epidemiologic studies. These results suggest that BlueSky forecasts can provide useful information for public health decision-making. Because the 2010 fire season was among the most extreme in the history of British Columbia, ongoing evaluation during typical fire seasons is needed to further validate the role of the BlueSky forecasts in public health protection.

References

BC Ministry of Environment. 2012. Envista - Air Resources Manager. Available: http://envistaweb.env.gov.bc.ca/ [accessed 22 January 2013].

BC Ministry of Health. 2013a. PharmaNet. PharmaNet. Available: http://www.health.gov.bc.ca/pharmacare/pharmanet/netindex.html [accessed 12 February 2013].

BC Ministry of Health. 2013b. Medical Service Plan. Medical Service Plan Home Page. Available: http://www.health.gov.bc.ca/msp/index.htm [accessed 12 February 2013].

BC Stats. 2011. Population Estimates, British Columbia and Sub-Provincial. Population Estimates, British Columbia and Sub-Provincial. Available: http://www.bcstats.gov.bc.ca/StatisticsBySubject/Demography/PopulationEstimates.aspx [accessed 12 February 2013].

Burrows WR, Vallée M, Wardle DI, Kerr JB, Wilson LJ, Tarasick DW. 1994. The Canadian operational procedure for forecasting total ozone and UV radiation. Meteorological Applications 1:247–265; doi:10.1002/met.5060010307.

Caamano-Isorna F, Figueiras A, Sastre I, Montes-Martínez A, Margarita Taracido, Piñeiro-Lamas M. 2011. Respiratory and mental health effects of wildfires: an ecological study in Galician municipalities (north-west Spain). Environmental Health 10:48; doi:10.1186/1476-069X-10-48.

Dennekamp M, Abramson MJ. 2011. The effects of bushfire smoke on respiratory health. Respirology 16:198–209; doi:10.1111/j.1440-1843.2010.01868.x.

Delfino RJ, Brummel S, Wu J, Stern H, Ostro B, Lipsett M, et al. 2009. The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003. Occupational and Environmental Medicine 66(3):189-197.

Dirksen RJ, Boersma KF, Laat J de, Stammes P, Werf GR van der, Martin MV, et al. 2009. An aerosol boomerang: Rapid around-the-world transport of smoke from the December 2006 Australian forest fires observed from space. J. Geophys. Res. 114:D21201; doi:10.1029/2009JD012360.

Dutkiewicz VA, Husain L, Roychowdhury UK, Demerjian KL. 2011. Impact of Canadian wildfire smoke on air quality at two rural sites in NY State. Atmospheric Environment 45:2028–2033; doi:10.1016/j.atmosenv.2011.01.072.

Elliott CT, Henderson SB, Wan V. 2013. Time series analysis of fine particulate matter and asthma reliever dispensations in populations affected by forest fires. Environmental Health 12:11; doi:10.1186/1476-069X-12-11.

Flannigan MD, Wagner CEV. 1991. Climate change and wildfire in Canada. Canadian Journal of Forest Research 21:66–72; doi:10.1139/x91-010.

Hajat S, Sheridan SC, Allen MJ, Pascal M, Laaidi K, Yagouti A, et al. 2010. Heat–Health Warning Systems: A Comparison of the Predictive Capacity of Different Approaches to Identifying Dangerously Hot Days. American Journal of Public Health 100:1137–1144; doi:10.2105/AJPH.2009.169748.

Henderson SB, Brauer M, Macnab YC, Kennedy SM. 2011. Three measures of forest fire smoke exposure and their associations with respiratory and cardiovascular health outcomes in a population-based cohort. Environ. Health Perspect. 119:1266–1271; doi:10.1289/ehp.1002288.

Johnston FH, Bailie RS, Pilotto LS, Hanigan IC. 2007. Ambient biomass smoke and cardio-respiratory hospital admissions in Darwin, Australia. BMC Public Health 7(1):240.

Lee T-S, Falter K, Meyer P, Mott J, Gwynn C. 2009. Risk factors associated with clinic visits during the 1999 forest fires near the Hoopa Valley Indian Reservation, California, USA. International Journal of Environmental Health Research 19(5):315-327.

Moore D, Copes R, Fisk R, Joy R, Chan K, Brauer M. 2006. Population health effects of air quality changes due to forest fires in British Columbia in 2003: estimates from physician-visit billing data. Can J Public Health 97:105–108.

Morgan G, Sheppeard V, Khalaj B, Ayyar A, Lincoln D, Jalaludin B, et al. 2010. Effects of Bushfire Smoke on Daily Mortality and Hospital Admissions in Sydney, Australia. Epidemiology 21(1):47-55 10.1097/EDE.1090b1013e3181c1015d1095a.

Mosca S, Graziani G, Klug W, Bellasio R, Bianconi R. 1998. A statistical methodology for the evaluation of long-range dispersion models: an application to the ETEX exercise. Atmospheric Environment 32:4307–4324; doi:10.1016/S1352-2310(98)00179-4.

Naeher LP, Brauer M, Lipsett M, Zelikoff JT, Simpson CD, Koenig JQ, et al. 2007. Woodsmoke health effects: a review. Inhal Toxicol 19:67–106; doi:10.1080/08958370600985875.

Pasken R, Pietrowicz JA. 2005. Using dispersion and mesoscale meteorological models to forecast pollen concentrations. Atmospheric Environment 39:7689–7701; doi:10.1016/j.atmosenv.2005.04.043.

Rappold AG, Stone SL, Cascio WE, Neas LM, Kilaru VJ, Carraway MS, et al. 2011. Peat bog wildfire smoke exposure in rural North Carolina is associated with cardiopulmonary emergency department visits assessed through syndromic surveillance. Environ. Health Perspect. 119:1415–1420; doi:10.1289/ehp.1003206.

Ruminski M, Kondragunta S, Draxler R, Zeng J. Recent Changes to the Hazard Mapping System. In: Proceedings of the 15th International Emission Inventory Conference, 15–18 May 2006. New Orleans, LA. 2006. Available: http://www.epa.gov/ttn/chief/conference/ei15/session10/ruminiski.pdf [accessed 1 August 2011]

Sakiyama S. 2013. The BlueSky Western Canada Wildfire Smoke Forecasting System. BC Air Quality. Available: http://www.bcairquality.ca/bluesky/BlueSky-Smoke-Forecasts-for-Western-Canada.pdf [accessed 3 January 2013].

Sapkota A, Symons JM, Kleissl J, Wang L, Parlange MB, Ondov J, et al. 2005. Impact of the 2002 Canadian forest fires on particulate matter air quality in Baltimore city. Environ. Sci. Technol. 39:24–32.

Sofiev M, Vankevich R, Lotjonen M, Prank M, Petukhov V, Ermakova T, et al. 2009. An operational system for the assimilation of the satellite information on wild-land fires for the needs of air quality modelling and forecasting. Atmos. Chem. Phys. 9:6833–6847; doi:10.5194/acp-9-6833-2009.

Statistics Canada. 2012. Dissemination area (DA) - Census Dictionary. Available: http://www12.statcan.gc.ca/census-recensement/2011/ref/dict/geo021-eng.cfm [accessed 22 January 2013].

Stein AF, Rolph GD, Draxler RR, Stunder B, Ruminski M. 2009. Verification of the NOAA Smoke Forecasting System: Model Sensitivity to the Injection Height. Weather and Forecasting 24:379–394; doi:10.1175/2008WAF2222166.1.

Tham R, Erbas B, Akram M, Dennekamp M, Abramson MJ. 2009. The impact of smoke on respiratory hospital outcomes during the 2002–2003 bushfire season, Victoria, Australia. Respirology 14(1):69-75.

US Department of Commerce. 2013. Hazard Mapping System Fire and Smoke Product - Satellite Services Division - Office of Satellite Data Processing and Distribution. Available: http://www.osdpd.noaa.gov/ml/land/hms.html [accessed 25 October 2012].

Viswanathan S, Eria L, Diunugala N, Johnson J, McClean C. 2006. An analysis of effects of San Diego wildfire on ambient air quality. J Air Waste Manag Assoc 56:56–67.

Wildfire management branch. 2013. Fire Averages. Available: http://bcwildfire.ca/History/average.htm [accessed 3 January 2013].

Wotton BM, Flannigan MD. 1993. Length of the fire season in a changing climate. The Forestry Chronicle 69:187–192.

Wotton BM, Nock CA, Flannigan MD. 2010. Forest fire occurrence and climate change in Canada. Int. J. Wildland Fire 19:253–271.

World Health Organization. Geneva: World Health Organization; 1975. International Classification of Diseases, 9th Revision.

Wu J, Winer A, Delfino RJ. 2006. Exposure assessment of particulate matter air pollution before, during, and after the 2003 Southern California wildfires. Atmospheric Environment 40:3333–3348; doi:10.1016/j.atmosenv.2006.01.056.

Table 1. Model evaluation statistics in global, spatial and temporal analyses comparing BlueSky and Monitor $PM_{2.5}$.

Analysis	IOA	r	NRMSE (%)	FB
Global analysis	0.53	0.40	18	-0.45
Spatial analysis (mean [range])	0.41 [0.02, 0.82]	0.32 [-0.17, 0.92]	66 [16, 538]	-0.91 [-2.00, 1.03]
Temporal analysis (mean [range])	0.46 [0.02, 0.80]	0.31 [-0.36, 0.86]	52 [20, 224]	-1.06 [-1.97, 1.30]

IOA = index of agreement, r = Pearson's correlation coefficient, NRMSE = normalized root mean squared error, FB = fractional bias.

Table 2. Rate ratio for each exposure metric (lag 0-1 in all cases). All models are adjusted for same-day maximum temperature, day-of-week, holiday and week-of-study. $PM_{2.5}$ values over 300µg/m^3 were truncated to 300µg/m^3 in Truncated BlueSky $PM_{2.5}$.

Exposure measures	Salbutamol dispensations	Asthma-related physician visits
BlueSky $PM_{2.5}$ (per 30µg/m^3)	1.08 (1.06, 1.10)	1.05 (1.01, 1.09)
Truncated BlueSky $PM_{2.5}$ (per 30µg/m^3)	1.11 (1.08, 1.13)	1.07 (1.02, 1.12)
Monitor $PM_{2.5}$ (per 30µg/m^3)	1.12 (1.07, 1.17)	1.10 (1.00, 1.21)
BlueSky Plumes (1 vs. 0)	1.05 (1.02, 1.09)	1.06 (0.99, 1.15)
HMS Plumes (1 vs. 0)	1.05 (1.01, 1.09)	1.09 (1.02, 1.18)

Figure Legends

Figure 1: Map of the BlueSky model domain and study area showing the local health areas (LHAs) and their health data availability, locations of the $PM_{2.5}$ air quality monitoring stations and locations of fire hotspots detected by the Moderate Resolution Imaging Spectroradiometer (MODIS) with fire radiative power (a measure of fire intensity) larger than 100 gigawatts. In the right panel, area with hatch pattern indicates LHAs with salbutamol dispensation data and area in purple indicates LHAs with asthma-related physician visit data.

Figure 2: Bland-Altman plot of BlueSky $PM_{2.5}$ comparing to Monitor $PM_{2.5}$ measurements, excluding all pairs with zero BlueSky predictions. The x-axis is the average of BlueSky forecasts and monitor measurements and y-axis is the difference between the two. The mean and confidence interval of the difference are indicated in the figures. Points above the zero in vertical suggest over-predictions from BlueSky compared with monitors.

Figure 3: Time series of daily model evaluation statistics. Green triangles indicate daily index of agreement (IOA) comparing BlueSky $PM_{2.5}$ and Monitor $PM_{2.5}$. Red dots indicate daily figure of merit in space (FMS) comparing BlueSky Plumes and HMS Plumes. The orange background indicates the major fire events during the study period.

Figure 4: Comparison of rate ratios estimated in very smoky and less smoky areas for salbutamol dispensations (left panel) and asthma-related physician visits (right panel).

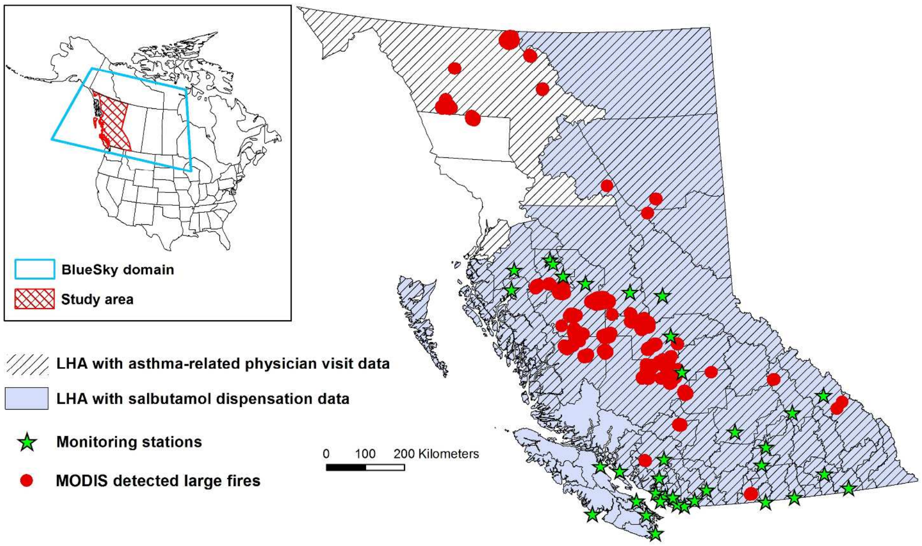

Figure 1

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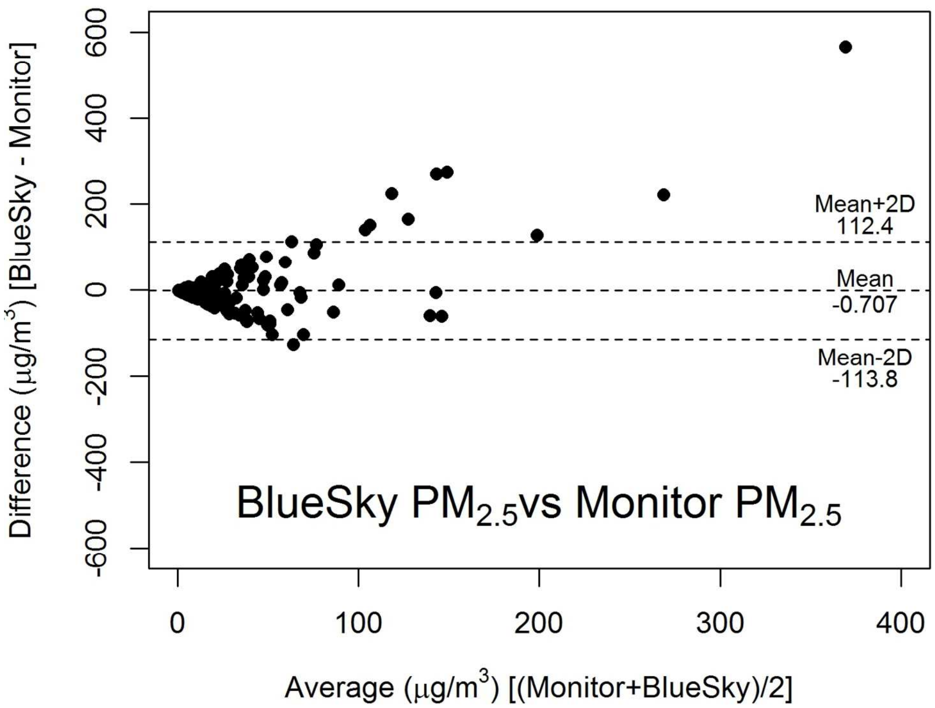

Figure 2
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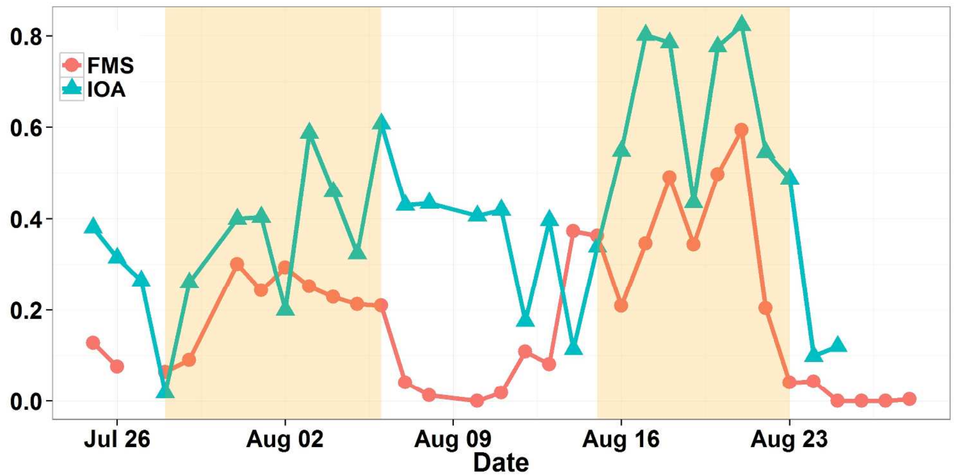

Figure 3
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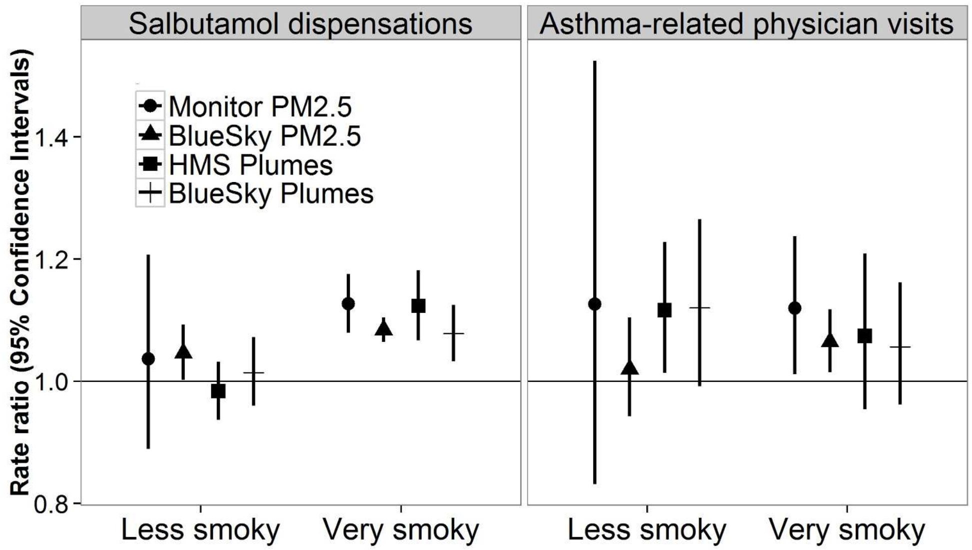

Figure 4
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